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AI and Health Disparities: An Analysis

We all know it's bad. We all know it's the beginnings of hard days, or rough nights, of lingering moments of worry impossible to put at bay by our bodies screaming and the doctors crying and our friends wondering whether every moment is our last. But our ability to rise up from illness is ultimately determined by our health care and the effort taken into allowing us to recover, and not everyone has that opportunity.

According to Healthy People 2020, health equity is defined as the "attainment of the highest level of health for all people"("Disparities"). Health equity means valuing everyone equally by addressing avoidable inequalities, historical and contemporary injustices, and the elimination of health and health care disparities. Health care disparities involve how many people have an illness, the severity of those illnesses, how many people die from the illness, whether health care is available, and how many people are screened and diagnosed with an illness. Health disparities are essentially the preventable differences to achieve optimal health experienced by socially disadvantaged populations typically discerned by sex, gender, ethnicity, sexual orientation, geography, income, level of education, or race. Statistics play an important role in approaching these problems logically and avoiding biases. In 2008, for example, about 33% of people identified as part of a socially disadvantaged population. Only 67% of people are free of the health disparities laced into our society; our ability to analyze these statistics and either reduce the significance of being part of a socially disadvantaged population or eliminate the social parameters which define certain groups as socially disadvantaged could impact our ability to survive as a species. As time goes on we find ourselves split over different religions, different cultures, different beliefs which can fracture our unity together and separate areas into war and peace, hate and disceptions; however, we tend to have trouble distinguishing the vastness of ideas or statistics without normalizing them down to terms we can understand. In History, for example, the entire history of the Earth is scaled down to a single year, a metric humans have experienced and understand in order to comprehend how small we are in the world when we appear in the last 25 seconds of the entire cosmic year("Disparities"). We need to transform data so we can understand it, and, in come cases, there are no methods of transforming simple facts such that every culture and every group understands the entire implications of a single idea or a single treatment. Artificial intelligence provides both a solution and a problem: AI is capable of predicting a patients' mortality, how to "facilitat[e] hospital benchmarking"(Johnson), "improve diagnoses, precisely target therapies, and leverage healthcare data"(Pocius). Unfortunately, in genomics researchers must be extremely careful because computer algorithms are based on data, data which is biased by a source's ability to obtain data. The Genome-Wide Association Studies(GWAS), for example, mostly have data pertaining to patients of Northern European descent; there are still large amounts of people from which we have very little genomic data. Pilar Ossorio, PhD, sounded the alarm regarding women's health and AI because data is driven off studies in which women have been "under-treated compared with men"(Pocius). Bias can enter AI from healthcare data, and bias can enter healthcare data by design and in its usage. If an algorithm is designed to earn more money for the company, biases can emerge. If an algorithm is utilized to learn mortality rates from data pertaining entirely to people of a certain race or descent, biases can emerge. Hospitals will spend $6.6 billion on AI and can ultimately save $150 billion in the healthcare economy, according to Accenture. AI is a "constellation of technologies from machine learning to natural language processing that allows machines to sense, comprehend, act, and learn"(Pocius).

Researchers such as Kevin Esvelt have proposed creating meetings, bridges between different beliefs and ideas pertaining to AI and its usage. At this point, researchers have specialized in the field of AI such that they do not necessarily have a background in ethics. Researchers do not understand the full implications of their actions and ideas, thus bringing together groups of researchers and outsiders promotes diverse thinking and methods of finding a solution to bring AI to the world safely. On September 20, 2019, researchers from Stanford joined with Dean Lloyd Minor, MD to observe the state of artificial intelligence in medicine.The talk features Jeanne Shen, a gastrointestinal pathologist working in Pathology AI research, Matthew Mungren, the assistant professor of radiology at Stanford, and Nigam H Shah, the associate professor of biomedical informatics working to bring AI to the world safely. They began by noting that it is important to define what we consider AI before beginning any ethical talks pertaining to AI. AI, according to Dr. Shah, is the use of any algorithms for the purpose of diagnosis and prognosis for patients; however, AI is used in other topics and its usage in medicine is relatively recent. AI is defined as any algorithm capable of interpreting data and providing an output without its algorithm explicitly defining the output. A computer solving the expression 1+2, for example, is not considered AI because its output is explicitly determined by the compiler. On the other hand, algorithms as simple as a tic-tac-toe player are considered AI because the algorithm's output is not explicitly dictated by its code. The researchers ultimately agreed AI is used to communicate ideas to the general public and can be classified into two major subcategories: narrow and general AI. General AI focuses on a wide variety of inputs and essentially learns to process information in a similar manner to a human and is capable of a wide variety of different tasks. Narrow AI, which all of the Stanford researchers worked with, teaches AI to do a very specific task very well. The growth of many AI technologies has exploded since the massive availability of data for the public despite having used AI since the early 80s. According to Dr. Shah, there are changes in incentive structures which suggest that, now that the data is out in the open, we have an obligation to use it, an idea which has also contributed to the significant growth of AI over the past few years. Another worry, however, when it comes to AI is the notion that it will take over our jobs in the future and only allow the rich to rise up while the poor are crushed by the simple AI capable of performing their tasks. The researchers note that, at least in the field of biology, algorithms automatically detecting diseases can perform faster and much more efficiently than a pathologist. Dr. Shen suggests this saves sime for pathologists to focus on more higher-level intellectual tasks such as synthesizing diagnostic information rather than looking for small indicators on a petri dish to diagnose a patient, a time-consuming task which could mean the difference between life or death in intensive care units(Chen). Ultimately the researchers concluded that AI will not put physicians out of business because humans have characteristics AI supposedly could never reproduce such as empathy. Furthermore, when we look at what a radiologist does rather than what an AI does, there are massive discrepancies. The AI has dedicated itself entirely to a single task, which it is extremely good at; however, there are other tasks which need to be completed beyond the diagnosis of a patient. This is an example of the paradox that occurs when we think about AI: in the short term, we tend to overestimate the effects of technology, worrying it will take away our jobs and our lives; on the other hand, in the longer term we underestimate the impact technology will have on us. As the amount of data available exponentially grows, we as humans need to focus more on the concepts and general ideas underlying certain technologies. Radiologists, for example, do not need to know how to make an MRI; however, they are expected to understand the concepts behind the machine and how it works. As the amount of data grows, students must specialize more as the field becomes larger and the ability to understand everything in that particular field becomes more difficult. On the other hand, however, our ability to grasp concepts and general ideas distinguishes us from AI capable of specific tasks. A balance of the two is essential for establishing equilibrium between us and AI("The State"); however, restoring balance is much harder when we are fighting against predetermined ideas of how much money to gain from creating new medicines or who has the ability to access new medicines versus who does not.

Cancer drug prices are too high. 2 billion people in the world don't have access to healthcare. 10 million people die every year of treatable diseases. Overall, we have an innovation pipeline that puts profit over patients, and it is a growing problem. AI in healthcare could potentially provide either a new perspective or merely deepin previous ties of inequity. It is a growing industry, promising to contribute about $16 trillion to the global economy; however, we tend to exaggerate the effects of AI in the short term and underestimate the effects in the long term. A prominent Stanford professor once stated: "It's just completely obvious that in five years deep learning is going to do better than radiologists"(Mathur). This statement sparked a lot of controversy in the radiologist community and a lot of backfire; however, we are asking the wrong question when we are wondering what AI will do in the future to jobs in healthcare. Once more, we are shielding our eyes to the very purpose of medicine, the very purpose of the field of biology: to help diagnose and treat patients. Rather than focusing on the jobs in healthcare, we should be focusing on how AI impacts patients' lives(Mathur).

We measure technology's success by looking at human welfare and how it impacts our lives; however, the problem still remains of how to hold these systems accountable for what they do, meaning that in the real world AI is not implemented very often due to the uncertainty surrounding these kinds of technologies, and once it is published, it often is in direct violation of the ethics we attempt to use as a filter(Mathur).

For example, a model was created to predict whether prisoners would commit a second crime to aid judges in their decision of whether to allow prisoners to leave prison. It scores the probability of them committing a second crime, summarizing an entire life into a single number. Unfortunately there is an implicit bias in our history towards African Americans, and that model was trained based on that data. The model labeled 44.9% African Americans as having a high risk of reoffending when they did not, while it labeled only 23.5% people of Caucasian descent as having a high risk of reoffending when they did not. 47.7% people of Caucasion descent were labeled as lower risk and 28% African Americans were labeled as lower risk and did reoffend. The algorithm proves racial bias, a kind of implicit bias in our history. Ultimately algorithms don't remove human bias. They amplify them(Mathur).

Another algorithm, known as "gaydar," was designed to classify whether someone was gay or straight entirely on their faces. The model worked with 81% accuracy and poses extreme privacy risks. Being able to walk past another person without any idea of who they are or what they've been through we are able to tell their sexual orientation, personal information which relies entirely on a model we don't understand and only works with 81% accuracy. Although the algorithm is currently under ethical review, it proposes the "black box" problem regarding neural networks. The mathematical complexity behind these algorithms makes their decisions impossible to understand. The "black box" refers to the idea that some kind of complex process we don't understand takes place and allows models to predict outputs with high accuracy. By creating this model, trust was broken, and trust is an inherent part of the patient-physician relationship. There aren't any steps to hold algorithms accountable if they predict a treatment incorrectly for a patient(Mathur).

There are steps we can take to address these issues such as building a task force. Unfortunately, simply the idea of allowing algorithms to access personal data brings up a privacy problem. Once more, according to Dr. Mathur, we must come together to form a discussion that brings together patients and computer scientists and physicians. We need to avoid black-box algorithms and find ways to discern their complexity such as feature maps. We need to be thinking about the next generation of data scientists as well. Ethics needs to become a part of the computer science curriculum - if computer scientists are looking to build ethical models, they must first understand the implications of those models(Mathur).

AI still generates trust issues among patients and healthcare consumers. 35% of people in a 2018 survey of 500 people said they were confident their data used for AI was confidential and being stored securely. 69% of consumers over 40 were concerned their data wasn't securely stored along with 58% of consumers younger than 40 worried about the same issue. Researchers suggest utilizing blockchain - a list of records linked together. Essentially each block contains a cryptographic hash of the previous block and other important features, making it impossible to directly modify any of the blocks and making data entirely secure. Aetna, Ascension, Humana, and Optum have been working together recently on the Synaptic Health Alliance, which uses blockchain to create a secure dataset.

Our current learning environment for neural networks is toxic; the best way to resolve these issues would be to focus on knowledge capture rather than knowledge retention, managing AI algorithms, and a better understanding of probabilities and how to apply them in decision making(Kent).

Ultimately the probabilities that AI generates are being shot down by skeptics; some argue that the statistics “gaydar” produced, for example, appear terrifyingly high because of the way the researchers structured the data. In retrospect, however, the researchers of gaydar admitted the experiment was designed entirely to spread awareness to the idea that the popularization of data can mean the reduction of privacy to ourselves. We need to begin thinking about ourselves as a species rather than single beings with single-minded opinions; our participation in studies such as these now not only breaches our own privacy but also breaches the privacy of others around us by allowing an algorithm the information necessary to classify different features taken from simply our faces. AI is tailored to those who have access to it and those who are part of the groups studied the most intensively by AI such as people of Northern European descent have an advantage in being given treatment plans more specified to our own genetic code. Are we being unfair, however, by pointing out the shortcomings in AI when doctors simulate the same processes? Doctors prescribe patients treatments depending on the results and effects they see from their own patients or from studies, both of which could be biased depending on the group or region the study took place. Ultimately we must proceed with extreme caution in the field of artificial intelligence; working on projects in this field is now a conjoined effort by different people in an effort to create artificial intelligence capable of providing beneficial changes to the healthcare system.

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